

SYSTEM IDENTIFICATION OF FLEXIBLE PLATE STRUCTURE

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*“To my supervisor, DR. INTAN ZAURAH MAT DARUS, your good deeds will
always be remembered.*

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ABSTRACT

This research presented an investigation into the performance of system identification using parametric and nonparametric techniques for the identification of a two-dimensional flexible plate structure. The input and output data of the flexible system were acquired through the experimental work using National Instrumentation data acquisition system and flexible plate test rig. A sinusoidal force was applied to excite the flexible plate and the dynamic response of the system was investigated. The parametric models of the system were developed through Recursive Least Square (RLS) and Genetic Algorithms (GA) methods; whilst the nonparametric models of the system were developed using Multi-layer Perceptron Neural Networks (MLP-NN), Adaptive Elman Neural Networks (ENN) and Adaptive Neuro-Fuzzy Inference System (ANFIS). The validity of the models was investigated based on statistical measures, mean square error and one step ahead output prediction. A comparative performance of all the approaches developed in this research was presented and discussed. It has been demonstrated that the best mean squared error for RLS was 0.0095 and for GA algorithm was 0.000562. This indicates the superiority of GA as compared to RLS for the parametric modelling approaches. For the nonparametric modelling of the system, the best mean squared error for MLP-NN, ENN and ANFIS were 0.000163, 0.001700 and 0.0003978, respectively. The results demonstrated that MLP-NN shows superiority as compared to ENN and ANFIS. The investigation also revealed that, comparing to all modelling techniques, MLP-NN performed the best in terms of convergence time to an optimum solution.

ABSTRAK

Penyelidikan ini mengkaji prestasi pengenalpastian sistem menggunakan teknik parametrik dan bukan parametrik untuk pengenalpastian model struktur plat fleksibel dua dimensi. Data masukan dan keluaran daripada sistem plat fleksibel dua dimensi diperolehi melalui ujikaji ke atas rig plat fleksibel dengan menggunakan sistem pengambilalihan data yang direka oleh National Instrumentation. Sebuah masukan daya sinusoidal digunakan untuk merangsang plat fleksibel dan kesan sambutan masa sistem dinamik ini dikaji. Model parametrik sistem ini dibangunkan dengan menggunakan kaedah Kuadrat Terkecil Rekursif (RLS) dan Algoritma Genetik (GA), manakala model bukan parametrik sistem ini dibangunkan dengan menggunakan Multi-layer Perceptron Neural Networks (MLP-NN), Adaptive Elman Neural Networks (ENN) dan Adaptive Neuro-Fuzzy Inference System (ANFIS). Pengesahan model dikaji berdasarkan ukuran statistik, purata kuasa dua kesalahan dan ramalan keluaran satu langkah di hadapan. Kemudian, perbandingan di antara semua teknik yang telah dibangunkan dalam kajian ini dibentangkan dan dibahaskan. Kajian mendapati bahawa keputusan bagi purata kuasa dua kesalahan menggunakan kaedah RLS adalah 0.0095 dan GA adalah 0.000562. Keputusan ini menunjukkan kaedah GA adalah lebih baik daripada RLS untuk pengenalpastian model menggunakan teknik parametrik. Untuk pengenalpastian model menggunakan teknik bukan parametrik, keputusan bagi purata kuasa dua kesalahan untuk MLP-NN, ENN dan ANFIS, masing-masing adalah 0.000163, 0.001700 dan 0.0003978. Keputusan kajian menunjukkan bahawa MLP-NN adalah lebih baik jika dibandingkan dengan ENN dan ANFIS. Selain itu, hasil kajian ini juga mendapati bahawa, diantara semua teknik pengenalpastian model struktur plat fleksibel dua dimensi yang telah dibangunkan, MLP-NN telah menghasilkan penyelesaian optimum yang terpanjang.

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LIST OF SYMBOLS

$A(z^{-1})$	Polynomials parameters of autoregressive
$B(z^{-1})$	Polynomials parameters of exogenous
$C(z^{-1})$	Polynomials parameters of moving average
$y(k)$	System output at time sample k
$u(k)$	System input at time sample k
$\xi(k)$	White noise at time sample k
\hat{y}	Estimation output at time t
n_y, n_u, n_e	Model orders
P_c	Crossover probability
P_1, P_2	GA parents strings
O_1, O_2	GA offspring strings
A_i, B_i	Linguistic label of ANFIS structure
z^{-1}	Back-shift operator
λ	Forgetting factor
$\phi_{ue}(\tau)$	Cross-correlation function between $u(t)$ and $e(t)$
O_k, O_j, O_i	Output values at the output, hidden and input layers
w_{kj}	Connection weight from unit j at the hidden layer to unit k at the output layer
w_{ji}	Connection weight from unit i at the input layer to unit j at the hidden layer
α	Momentum factor
η	Learning rate
δ_k	The error signal from the NN output to the hidden layer
δ_j	The error signal from the hidden layer to the input layer

LIST OF ABBREVIATIONS

RLS	Recursive Least Square
GA	Genetic Algorithm
MLP-NN	Multi-layer Perceptron Neural Networks
ENN	Elman Neural Networks
ANFIS	Adaptive Neuro-Fuzzy Inference System
NI	National Instrumentation
OSA	One step ahead
MSE	Mean squared error
NNs	Neural networks
TRMS	Twin rotor multi-input multi-output system
FD	Finite Difference
ARMAX	Autoregressive moving average model with exogenous inputs
NARMAX	Non-linear autoregressive moving average model with exogenous inputs
ARX	Auto Regressive with exogenous inputs
NARX	Non-linear Auto Regressive with exogenous inputs
FL	Fuzzy Logic
RBF	Radial-Basis Function
BP	Backpropagation
RNNs	Recurrent Neural Networks
FIS	Fuzzy Inference System
SISO	Single-Input Single-Output
DAQ	Data Acquisition System

A/D	An analog to digital converter
D/A	Digital to an analog converter

CHAPTER 1

INTRODUCTION

1.1 Introduction

The use of flexible structures in many engineering applications is expanding rapidly. The basic elements for flexible structural analysis are plates, beams, frames and shells. These elements are used in a broad range of engineering applications and particularly in aeronautical, mechanical, marine, aerospace, civil engineering and many more.

Plates with different shapes, boundary conditions at the edges, and various complicating effects have often found applications in different structures such as aerospace, machine design, telephone industry, nuclear reactor technology, naval structures, and earthquake-resistant structures. In particular, the dynamic behaviour of flexible, flat, thin, rectangular plates is a subject that has received considerable attention in recent years because of its technical importance [1].

The thickness dimension of the plate is much smaller than its planar dimensions yielding a “thin-walled” type of structure. In cases the plate is subjected

to in-plane loading, it exhibits a range of physical effects that are associated with the stability of the structure and lead to high vibration. Vibration of flexible structures may cause reduced system effectiveness, structural fatigue and human discomfort. This is a major reason why the vibration of flexible structure needs to be controlled [1].

To control the vibration of a plate effectively, it is often required to obtain an accurate or approximate model of the plate structure, which will result in good control. Thus, finding an appropriate model of a dynamic system, such as a thin plate, would be the key to design an effective controller to suppress the vibration in the plate [2].

Vibration analysis of plates in various shapes and configurations has been studied extensively in the past. In the initial stages of these studies, the results were only available for some simple cases, such as with a limited set of boundary conditions and geometries, in which the analytical solution could be easily found. The lack of good computational facilities made it almost impossible to get accurate results even in these cases. With the advent of fast computers and various efficient numerical methods, there has been a big increase in the amount of research done to get a better accuracy in the results. Numerical methods offer reasonable and acceptable solutions, but with complex shapes of plate structure, sometimes it leads to inaccuracies and requires more computing time [1].

In order to control the physical system or to predict its behaviour under different operating conditions, a model can be created using an approach called System Identification. The main objective of System Identification is to find an accurate or an approximate model of system dynamics based on the observed inputs and the outputs.

1.2 Problem Statement

Several researchers have applied methods to solve the System Identification problems. A number of techniques have been devised to determine models that best describe the input and the output behaviour of a system. Ismail, *et. al.*, have reported identification algorithms of flexible structure using Neural Networks. The Research investigated the development of System Identification approach in the modelling of the dynamic of a two dimensional flexible plate structures [3]. Besides, Tavakolpour, *et. al.*, have reported the performance evaluation of Genetic Algorithm for System Identification of a flexible structure [4]. Ismail, *et. al.*, have reported the dynamic characterisation of flexible vibrating structures using Adaptive Neuro-Fuzzy Inference System (ANFIS) [5]. All these researches conducted System Identification using simulated data and each one of these previous researches used only one technique in their research. The input-output data of the flexible plate structure in all of the above mentioned researches was acquired through the simulation studies only using finite difference method [3, 4, and 5]. This has greatly restrained the general ability of the validity of their research findings in real life application. Moreover, their research works concentrated in the performance evaluation of only one System Identification approach.

Therefore, in this study a number of System Identification approaches, namely the Recursive Least Square (RLS), Genetic Algorithms (GA), Multi-layer Perceptron Neural Networks (MLP-NN), Adaptive Elman Neural Networks (ENN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) were applied to the flexible plate structure using experimental data. The performance of these approaches in the modelling of flexible plate structure was also validated and compared between each other.

1.3 Objective

The objective of this study is to develop a model that characterises the vibration of a two-dimensional flexible rectangular plate structures using parametric and nonparametric identification techniques.

1.4 Scope of Study

The scopes of the research are as follows:

1. Use of experimental test rig and National Instrumentation Data Acquisition System to obtain the vibration data of the flexible plate.
2. Parametric modelling of the vibration of the flexible plate structure using conventional parametric modelling approach with RLS and intelligent parametric modelling approach with GA.
3. Nonparametric modelling of the vibration of the flexible plate structure using intelligent nonparametric modelling approach with MLP-NN, ENN and ANFIS.
4. Validation of all the developed models using one step-ahead prediction, mean squared error and correlation tests.
5. Comparative assessment of all the models.

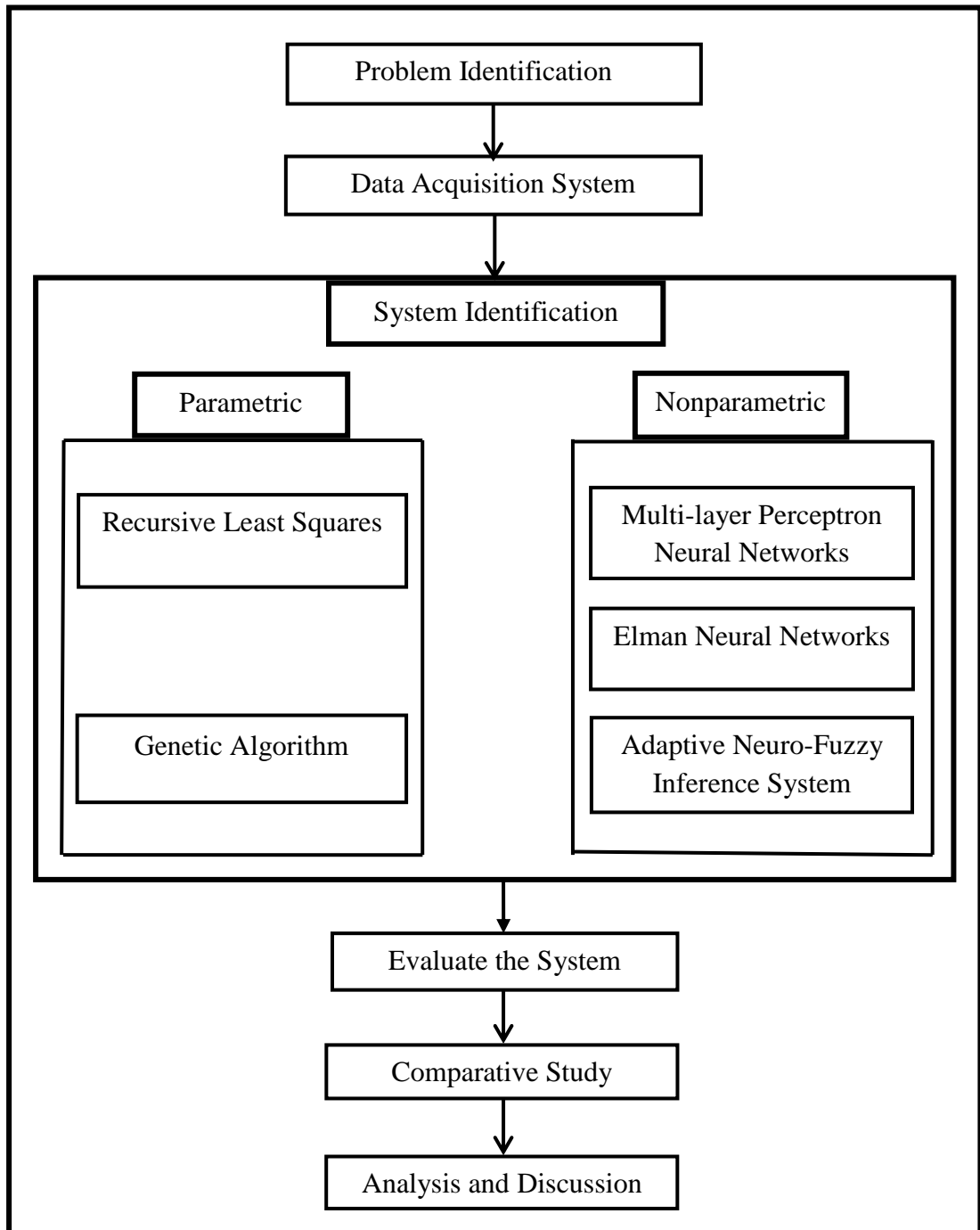


Figure 1.1: The flow chart of the project